Texture Analysis for Skin Classification in Pornography Content Filtering Based on Support Vector Machine

Hanung Adi Nugroho*, Fauziazzuhry Rahadian, Teguh Bharata Adji, Widhia K.Z. Oktoeberza & Ratna Lestari Budiani Buana

Department of Electrical Engineering and Information Technology
Faculty of Engineering, Universitas Gadjah Mada
Jalan Grafika No. 2, Yogyakarta 55281, Indonesia
*E-mail: adinugroho@ugm.ac.id

Abstract. Nowadays, the Internet is one of the most important things in a human's life. The unlimited access to information has the potential for people to gather any data related to their needs. However, this sophisticated technology also bears a bad side, for instance negative content information. Negative content can come in the form of images that contain pornography. This paper presents the development of a skin classification scheme as part of a negative content filtering system. The data are trained by grey-level co-occurrence matrices (GLCM) texture features and then used to classify skin color by support vector machine (SVM). The tests on skin classification in the skin and non-skin categories achieved an accuracy of 100% and 97.03%, respectively. These results indicate that the proposed scheme has potential to be implemented as part of a negative content filtering system.

Keywords: *negative content; pornography; skin analysis; support vector machine; texture feature.*

1 Introduction

Technology is developing rapidly in order to make things easier in every aspect of human life. One of the most important fast growing technologies is the Internet. The Internet is used to connect and link people through a huge variance of information. However, the information may contain both positive and negative content. Negative content may consist of images that contain pornography. The Indonesian government screens negative content through Rule of the Ministry of Communications and Information Technology (*Permenkominfo*) of the Republic of Indonesia Number 19, 2014 regarding the Handling of Negative Content on Internet Sites [1]. Article 4 of *Permenkominfo* No. 19, 2014 provides a clear definition of negative content on Internet sites that contain pornography, activities that are illegal by legislation and other illegal activities reportable to the Government.

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A smart system utilising image processing can be built to prevent negative content leakage. Negative content filtering systems based on image processing have been developed in several studies focusing on detection of a combination of body parts, such as face, breasts and genitals.

Wang, *et al*. [2] applied Viola Jones classification to detect nipple areas. Unfortunately, a number of false positives were detected in the eyes and navel areas. Zuo, *et al*. [3] used a combination of Viola Jones classification and skin detection in YC_bC_r color space to detect pornographic images. A localisation function to calculate the skin area ratio was not considered in this approach; the used images were merely limited to naked images and could not be applied to bikini images.

Santos, *et al*. [4] employed skin segmentation using GLCM features on YC_bC_r color space. This approach was able to separate skin objects from similar-to-skin color objects based on a linear discriminant analysis (LDA) classifier. However, this method has the disadvantage that the pornographic object must be located in the centre of the image. A combination of RGB and YC_bC_r color space was used in [5] to detect pornographic videos based on skin segmentation. YC_bC_r color space was also used in [6] to detect skin areas. Pornographic images were classified based on the ratio between skin area and whole image. However, skin texture analysis was not involved in this approach and the method was not tested on images at low light conditions.

Bouirouga, *et al*. used the ANN threshold to detect pornographic images by detecting the skin area in YC_bC_r color space [7]. Some detected false positives were eliminated using background subtracting. Unfortunately, this approach can only be used on images that provide a reference image. A deep-learning based approach was applied in [8] to classify pornographic images and videos.

Adji, *et al*. [9] classified negative content filtering based on skin texture features. Karavarsamis, *et al*. proposed pornography detection using the convex hull for localisation of skin [10]. In their method, the skin region of interest is determined and compared to the whole body region. Classification of pornography is conducted based on the ratio between these two regions. However, skin classification is not conducted based on texture analysis, which may lead to false classification of non-skin objects, such as wood and sand that have a texture similar to that of skin.

The present research was aimed at developing a technique to classify skin in digital images. To improve the classification results, a face detection algorithm is applied in order to exclude the face area in the classification process. The scheme was implemented on three kinds of image categories, i.e. pornography, skin and non-skin images. This paper is organised in four sections. Section 1 describes the background of the research problem. Section 2 explains the proposed scheme, consisting of face detection and skin classification. Results and analysis are described in Section 3, followed by the conclusion in Section 4.

2 Approach

The approach used in this study can be divided into two main stages. First, the training stage, which is used to find the features and threshold values for the skin classification. The second stage is dataset testing, which is conducted to test the accuracy of the skin classification. Both phases are shown in Figure 1.

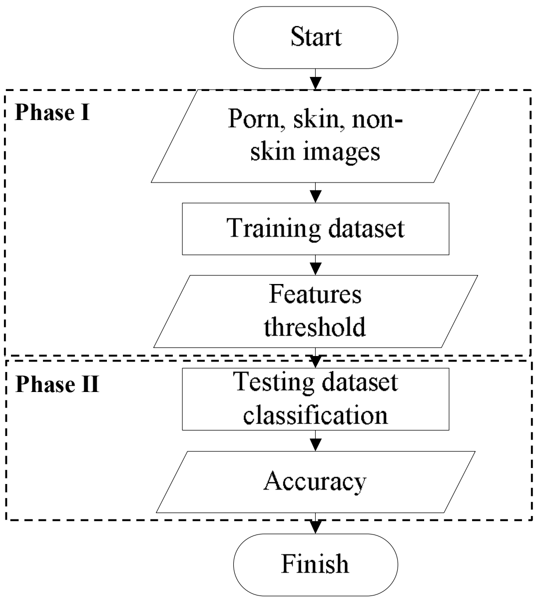


Figure 1 Flowchart of approach.

2.1 Materials

In this research, the data were collected from the Internet. The total number of data was 810 images in RGB format. The data were divided into two classes, i.e. the training and the testing dataset for two categories, namely 'skin' with 135 images and 'non-skin' with 415 images.

2.2 Training Phase Dataset

The training dataset is used to obtain features and the threshold value as parameters for classifying skin and non-skin images. The detailed steps for the training dataset are depicted in Figure 2.

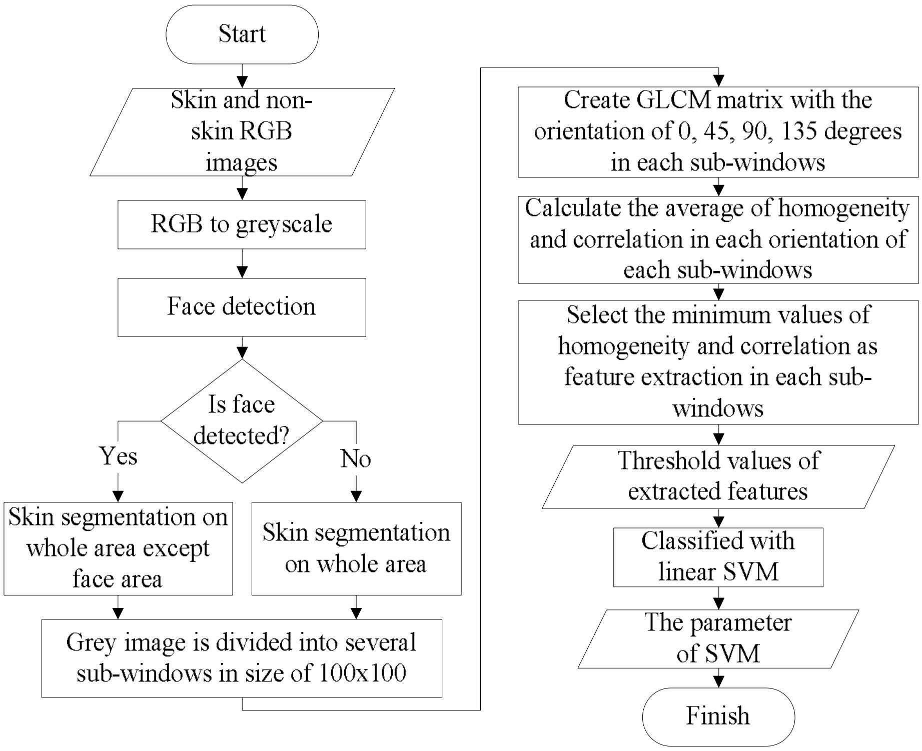


Figure 2 Flowchart of training dataset.

The input images for the training dataset are skin and non-skin images, which are converted from RGB to grey-scale using Eq. (1) in order to facilitate the face detection process, as shown in Figure 3. In Eq. (1), Y represents intensity in grey-scale, while R, G and B represent intensity in red, green and blue.

Face detection was conducted based on the Haar-like features of the Viola Jones algorithm to eliminate the facial area, as described in Figure 4. The facial area consists of a number of components, such as eyebrows, mouth and eyes, that can affect the analysis of skin texture. Therefore, if a face area is detected, it should be removed from the skin area.

$$Y' = 0.299R + 0.587G + 0.114B \tag{1}$$

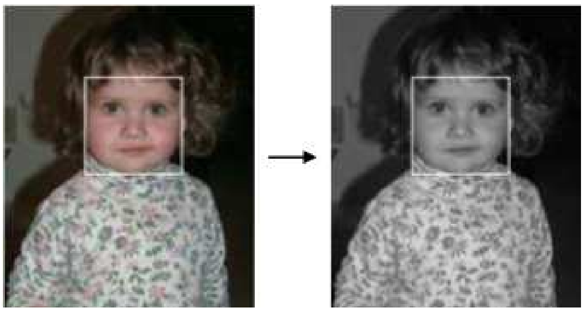


Figure 3 Conversion result of RGB to greyscale.

Figure 4 Face detection based on Haar-like features of Viola-Jones algorithm.

The next step is feature extraction, which is conducted by using grey level co-occurrence matrices (GLCM). GLCM is a second-order statistic measurement and contains information about pixel positions with similar grey level values. GLCM was first proposed by Haralick in 1973 [11]. GLCM contains several features, namely contrast, entropy, correlation, homogeneity, cluster shade and cluster prominence, as formulated in Eqs. (2) to (7).

$$\text{Contrast} = \sum_{n=1}^{L} n^2 \left\{\sum_{|i-j|=n} GLCM(i,j)\right\} \tag{2}$$

$$\text{Homogeneity} = \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{GLCM(i,j)}{1+(i-j)^2} \tag{3}$$

$$\text{Entropy} = -\sum_{i=1}^{L} \sum_{j=1}^{L} (GLCM(i,j)) \log(GLCM(i,j)) \tag{4}$$

$$\text{Correlation} = \frac{\sum_{i=1}^{L} \sum_{j=1}^{L} (ij)(GLCM(i,j)) - \mu_i' \mu_j'}{\sigma_i' \sigma_j'} \tag{5}$$

$$\text{Cluster shade} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i + j - \mu_x - \mu_y)^3 \; x \; P(i,j) \tag{6}$$

$$\text{Cluster prominence} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i + j - \mu_x - \mu_y)^4 \; x \; P(i,j) \tag{7}$$

Here, *P(i, j)* is the normalised grey-tone spatial-dependence matrix. Mean and deviation of GLCM *(i, j)* are expressed as μ_i', μ_j' and σ_i', σ_j', respectively.

Having been extracted using GLCM, the grey-scale image is divided into several sub-windows with a resolution of 100 x 100 pixels for each sub-window, as depicted in Figure 5. GLCM matrices are created with orientation at 0, 45, 90 and 135 degrees for each sub-window. Each orientation extracts the features of homogeneity and correlation, and then the average of these features for each sub-window is calculated. The minimum values of homogeneity and correlation for all sub-windows are determined and used as the threshold values for classification. These threshold values are used to determine the parameters for the linear SVM classification. Linear SVM classification boundary attributes can be issued in the form of equation $y = a(x) + c$, as shown in Figure 6.

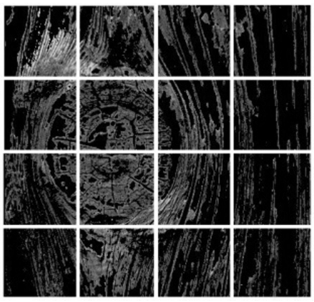


Figure 5 Example of GLCM analysis in multiple-window image.

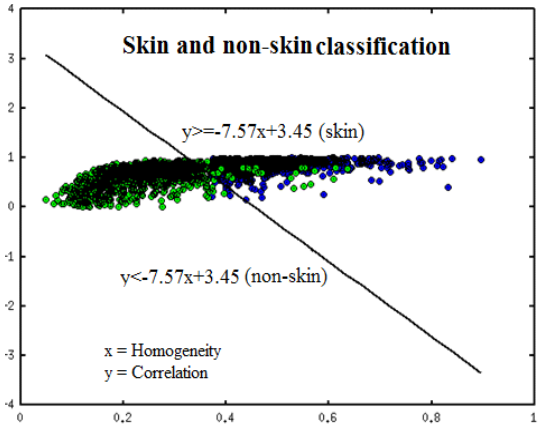


Figure 6 Attributes of skin classification.

An image is categorised as skin if $y >= -7.57x + 3.45$ and categorised as non-skin if $y < -7.57x + 3.45$. Here, x is homogeneity and y is correlation.

The classification is evaluated by measuring accuracy, which involves four parameters, i.e. true positives (*TP*), false positives (*FP*), true negatives (*TN*) and false negatives (*FN*). TP is correct identification, i.e. a skin image is classified as skin. FP is incorrectly accepted, i.e. a non-skin image is classified as skin. TN is correctly rejected, i.e. a non-skin image is classified as non-skin. FN is incorrectly rejected, i.e. a skin image is classified as non-skin. Accuracy is the percentage of true results from the total number of items [12] as formulated in Eq. (8) [13]:

$$\text{Accuracy} = \frac{(\text{TP+TN})}{(\text{TP+TN+FP+FN})} x\ 100\% \tag{8}$$

2.3 Testing Phase Dataset

The testing dataset consists of skin and non-skin images taken in good lighting conditions. In general, the testing process is similar to the training process. The difference is in the step in which the features extracted by GLCM are compared to the threshold values, as shown in Figure 7.

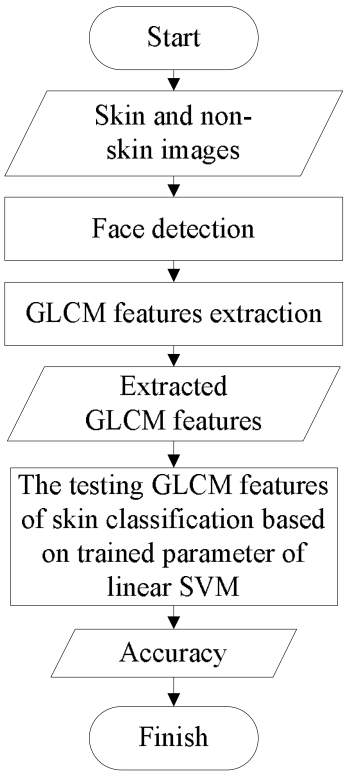


Figure 7 Flowchart of dataset testing.

The accuracy of skin classification is obtained from the testing of skin and non-skin classification based on the linear SVM classifier. If the GLCM features exceed the parameters of linear SVM, the image is classified as skin. Otherwise, it is classified as a non-skin image. The accuracy of linear SVM classification is determined by its ability to correctly classify images as skin and non-skin.

3 Results

3.1 Training Phase Dataset

The training phase is aimed at obtaining a threshold value based on the GLCM texture features, i.e. homogeneity, correlation, entropy, energy, cluster shade and cluster prominence. After that, the mean value of these features is calculated and compared. The results are shown in Figure 8.

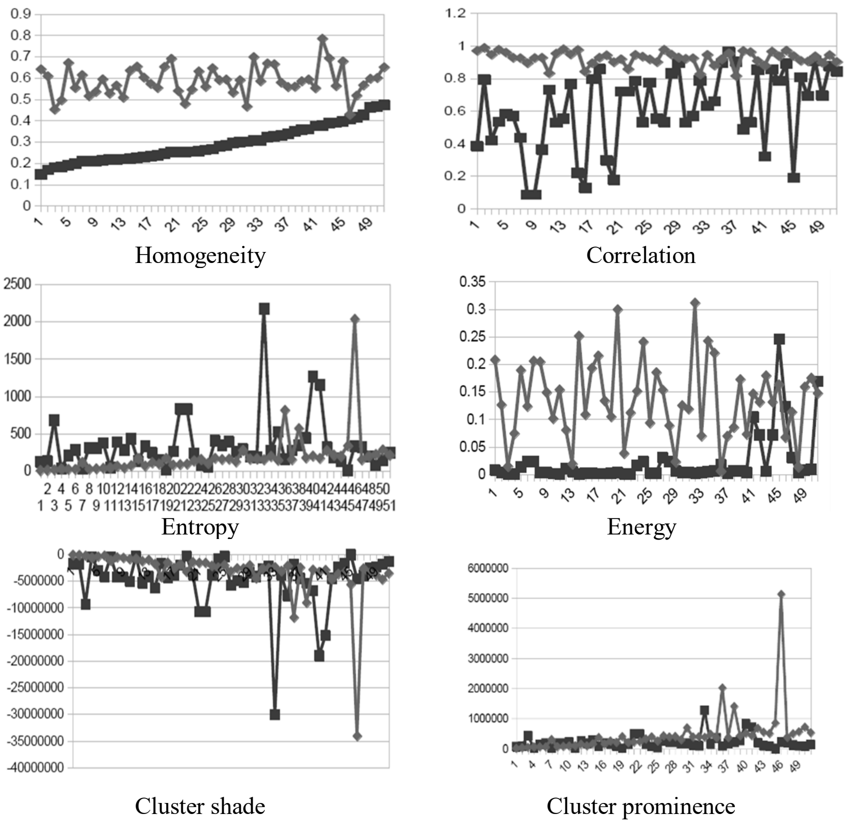
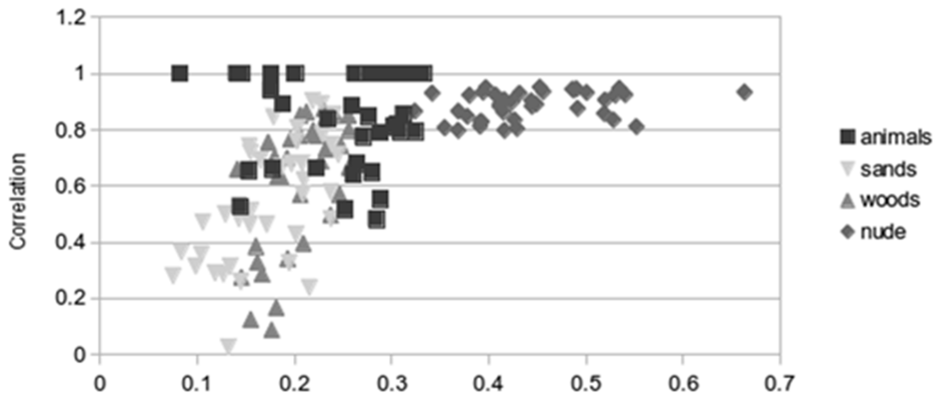


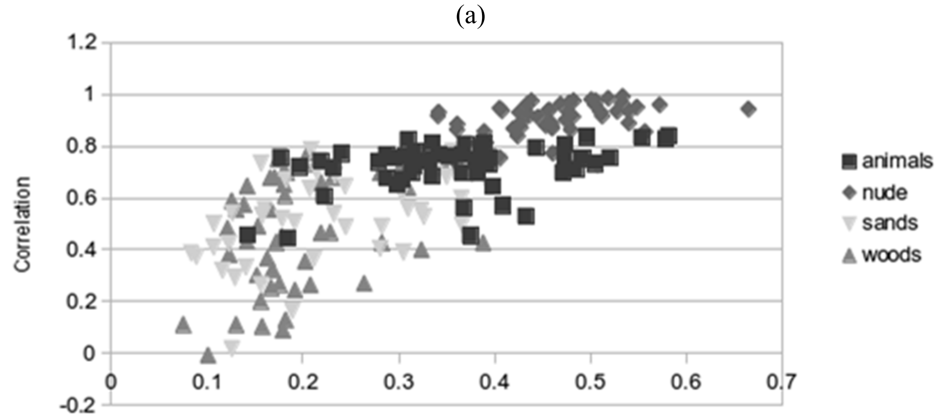
Figure 8 Comparison of mean values of GLCM features over 50 samples images, nude (◆) and wood (■).

Figure 8 shows a comparison of the mean values of homogeneity, correlation, entropy, energy, cluster shade and cluster prominence after training on 50 samples of nude images that represent the skin category and 50 samples of wood images that represent the non-skin category. The mean values of homogeneity and correlation are non-similar between the nude-image data and the wood-image data, whereas the mean values of energy, entropy, cluster shade and cluster prominence of both image types have similar values. Hence, homogeneity and correlation are reliable GLCM features to use for classification of images based on their mean threshold values.



Homogeneity

(a)



Homogeneity

(b)

Figure 9 (a) Spread of minimum values from correlation (y) and homogeneity (x); (b) spread of minimum deviation from correlation (y) and homogeneity (x) for pornography (◆), sand (▼), wood (▲) and animal (■) image categories.

To reach a good understanding of the classification process, the minimum values of homogeneity and correlation for 50 sample images were analysed as presented in Figure 9(a). Meanwhile, Figure 9(b) shows an analysis of the minimum deviation values from homogeneity and correlation. The minimum deviation value is defined as subtraction of the mean value from its standard deviation. However, the lower deviation values as shown in Figure 9(b) do not provide a clear distinction between skin and non-skin feature values. From both figures it can be concluded that skin classification using the minimum value of homogeneity and correlation is better than using the minimum deviation value.

3.2 Testing Phase Dataset

The input dataset is then tested and analysed using the selected GLCM texture features, i.e. homogeneity and correlation, in order to distinguish between skin and non-skin images. Beforehand, each image is divided into several sub-windows with a resolution of 100 x100 pixels. The homogeneity and correlation values are obtained for each sub-window.

After the texture features are extracted, the classification process is executed based on the SVM parameters from the training stage to classify the image as skin or non-skin. If an extracted feature value is equal to or more than the threshold value, then the image can be classified as skin and vice versa, as presented in Figure 10.

Figure 10 Skin segmentation result based on SVM parameters (some body parts are covered for decency).

Several classification methods, i.e. Naïve Bayes [14], linear discriminant analysis (LDA) [15], quadratic discriminant analysis (QDA) [16] and support vector machine (SVM) [17], were performed to evaluate the proposed scheme. A comparison of skin data testing results is presented in Table 1.

Table 1 Skin classification using 135 sample images.

Image Category		QDA (%)	LDA (%)	Naïve Bayes (%)	SVM (%)
Skin		0	0	100	**100**
Non-skin	**Sand**	100	85.85	0	**96.3**
	Animals	99.25	91.09	0	**96.3**
	Wood	100	91.85	0	**98.5**

Overall, SVM successfully classified the skin images in all categories and outperformed the other classification methods. The average accuracy achieved by SVM in classifying skin and non-skin images (sand, animals, wood) was 100% and 97.03%, respectively.

4 Discussion and Conclusion

A scheme for classifying skin images was developed. The data input consists of skin and non-skin images taken in good lighting conditions. This study used reduction of false skin segmentation based on the GLCM texture features homogeneity and correlation, followed by linear SVM classification. This was not done in related studies, such as by Wang, *et al.* [2], Karavarsamis, *et al.* [10], Basilio, *et al.* [6]. Santos, *et al.* used GLCM features based on LDA classification [4].

By extracting a number of texture features from the training dataset, the SVM parameters can be determined to classify the testing dataset. The results showed that the accuracy achieved by SVM in skin classification was 100%. This means that the number of correctly classified images was 135 out of a total of 135 images. The accuracy for the non-skin category (sand and animals) was 96.3%, which means that the number of correctly classified images was 130 out of a total of 135 images. Meanwhile, for the wood category, the achieved accuracy was 98.5%, meaning that 133 images were correctly classified out of a total of 135 images. Hence, the average level of accuracy for the non-skin category was 97.03%.

Based on these findings, the proposed scheme is not only able to correctly classify skin, but also to differentiate skin from objects similar to skin, such as wood and animal fur. In other words, the scheme successfully solves the problem of false skin segmentation. Hence, it has potential to be implemented for filtering negative content in the form of digital images.

However, for real application as part of a digital negative content filtering system, further research work needs to be done, based on a greater number of image datasets. Based on the current successful findings, the proposed scheme may also be further developed for negative content filtering of videos.

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